MathWorks Math Modeling Challenge 2020
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M3 Challenge RUNNER UP—$15,000 Team Prize

JUDGE COMMENTS

This was a highly regarded paper, and the team provided good models with a strong analysis of their models. There are some areas in which the paper could be improved, though. For example, the writing was not easy to follow in some places, and more consistent editing would have been beneficial. Related to this concern, in some places the calculations were presented in a way that was difficult to parse in places, and a more consistent presentation of the intermediate calculations would be an aid to the reader to better follow the team's excellent efforts.

The team did perform some excellent modeling, however, and it did come through in their presentation. The models were appropriate, and the team did a very good job reflecting on how the models could be improved. Additionally, the team had important insights into the relative balance and relationships between internal combustion vehicles and electric vehicles and were able to develop models consistent with those insights. Finally, the team recognized that trucks would unlikely be fully charged at each stop and created a model that accommodated that insight.

The judges had a number of questions regarding this entry:

1. Question one: the team used 79100 as the carrying capacity (production limit) of Telsa's Model 3. Had the team considered to use a higher number than 79100? The sales of Model 3 accelerated in 2019, and a higher carrying capacity number could be justified although the federal tax credit reduction in 2020 definitely affected sales.
2. The team assumed that the projections stated by the CEO of the Tesla Corporation would hold true and that the sales would follow production numbers made in comments. What other methods could be used to obtain an estimate? How much trust can be put in the CEO's comments?
3. The adoption figures were calculated using the sum of quarterly production, and the individual quarters were found using logistic models. Why not just use one logistic model over the whole time span?
4. Question two: How were the AADTT values on each route calculated? How were the maximum values and estimates for the number of trucks that will require recharging during a day on each route calculated, and how much trust do you have in the calculations? The same note applies to the peak and non-peak hours.
5. Question three: The team found a number of different factors and then calculated a Z-statistic for the numbers. The individual numbers were found from different considerations. Why can they be added? Also, why should they be normalized by the standard deviation of the unrelated numbers?
6. Question 3, Assumption 1: Discuss more specifically the "sampling data" that you refer to. Also, discuss how you are applying the Central Limit Theorem to this context. What method of "sampling" did you use?

Stuck with Trucks? Anticipate an Up*tick* in Elec*trick*

Executive Summary

        The trucking industry is a necessary component of the United States economy, and its importance is only growing in an age reliant on shipping giants like Amazon and FedEx. However, diesel fuel economy is grossly inefficient, with a national average of 5.98 miles per gallon (mpg) [1]. In 2017, transportation emissions accounted for 29% of the total greenhouse gas (GHG) emissions, with 23% of those emissions caused by medium- and heavy-duty trucks (6.7% of total GHG emissions) [2]. A switch to alternative energy that does not increase emissions would represent a significant decrease in GHG emissions, a step in the right direction towards preventing climate change and preserving the world's fuel resources for the future.

        If the trucking industry were to integrate electric vehicles into the fold of its transportation, we would want to predict the growth of electric semis in service on the road for the near future. How many trucks will be *electrified* in 5, 10, and 20 years? In our calculations, we found that given the infrastructure for a seamless transition to electric vehicles was in place, the purchasing of electric semis was a better investment than purchasing diesel semis in all cases. Thus, we computed the amount of diesel semis that expired each year and modeled the introduction of electric semis to the market with a robust modified logistic model. Our model then iterated through each year, replacing diesel semis with electric semis. Through this method, we found, in 5, 10, and 20 years, electric semis will compose 34.6%, 79.6%, and 92.4%, respectively, of all semis in commission.

        The transition from diesel to electric not only involves replacing the vehicles. Electric semis require long charging times at specialized charging stations. Exactly how many would we need along a major freight route? How many chargers per station? We used real-world statistics such as ideal battery usage ranges and traffic volume data to model the parameters that would satisfy all of the trucks' charging needs. For our model, we used a linear evaluation of distance to find the number of stations needed in the corridor and a linear evaluation of traffic density to find the number of chargers needed at each station. For the sample trucking corridors of Los Angeles to/from San Francisco, Boston to/from Harrisburg, Minneapolis to/from Chicago, San Antonio to/from New Orleans, and Jacksonville to/from Washington D.C., our model predicts that the number of stations and chargers per station needs to be 12 and 16, 12 and 15, 13 and 12, 16 and 17, and 20 and 9, respectively. With our model, a semi should never be further than 45 minutes away from a charging station based on average semi highway speeds.

        However, it is not enough to just ponder the potential effects of increased electric trucking: we need to actually implement the changes on an industrial scale. But where do we start with our diesel to electric initiatives? To maximize the benefit of electric transportation, trucking corridors where the total positive impact is greatest should be prioritized. Our model is a score metric derived using z-transformations. To gauge the magnitude of the positive effect, we considered multiple factors: Public Support, Carbon Emissions Cost, Projected Development Cost, and Usage. For our model, we converted each individual factor statistic into a z-score and aggregated all four z-scores to obtain a Monetary Index score. The corridor with the highest index score should have the transition to electric trucking implemented first. Based on the five corridors given, the San Francisco to/from Los Angeles route has the highest index, followed by the Texas to/from Louisiana route, the Florida to/from Washington D.C. route, the Massachusetts to/from Pennsylvania route, and last, the Minnesota to/from Illinois route.

Problem #1

A. Background

Electric semis provide an environmentally friendly alternative to the current diesel-dependent, low-efficiency semis used for shipment today. With the upfront cost-barriers lowered to competitive prices compared to popular diesel-based models (~$180,000 for the Tesla Semi compared to ~$120,000 for the average Class 8 semi) as well as the increasing efficiency of electric energy (equivalent to ~52 mpg compared to diesel's 5.98-7.3 mpg), electric vehicles appear appealing to shipping companies like FedEx, PepsiCo, and UPS [3, 4]. These costs are likely to continue declining as the electric semi sector becomes more competitive. Additionally, the switch to electric presents an opportunity to increase the public image of a company in contrast to the heavily polluting diesel semis. As battery technology continues to progress and the cost of charging decreases, it is reasonable to predict that companies will increasingly shift to the more cost-efficient battery electric vehicles (BEVs).

B. Definitions

1. <u>Semi</u>: abbreviated term for semi-truck
2. <u>Short Haul (SH)</u>: semis that operate within a 50-mile radius of their home terminal, 5% of all semis
3. <u>Regional Haul (RH)</u>: semis that operate within a 300-mile radius of their home terminal, 45% of all semis
4. <u>Long Haul (LH)</u>: semis that operate within a 500-mile radius of their home terminal, 50% of all semis

C. Restatement of the Problem

Assuming complications with charging stations, public support, drivers, and other aspects of electric vehicle infrastructure, we must construct a mathematical model to determine the percentage of semis that will be electric in 2025, 2030, and 2040. To do this, we must consider the lifetime of the vehicle, the upfront cost of both types of semis, the dollar cost per mile of the vehicle during operation, and the current production rate of diesel semis.

D. Assumptions and Justifications

1. Trucking companies will only replace diesel trucks that naturally go out of commission due to expiration.
   - Not only would it be economically disadvantageous for the companies to replace functioning assets that they already invested money in, but that would also introduce opportunity cost considerations that would unnecessarily complicate the model.
2. The diesel semis will be retired after 12 years of service [1].
   - There is no need to complicate the model by considering the number of semis that are retired early or late because, on average, semis are retired after 12 years.
3. Electric semis will be retired after 1,000,000 lifetime miles.
   - This value is stated by Tesla when they unveiled their line of electric semis [5].
4. Diesel fuel and electricity prices stay the same over the course of the drive.
   - Although fuel and electricity prices will vary slightly among regions and states, the national average is around $2.853 per gallon for diesel fuel and $0.12 per kWh for electric [6, 7], which we can apply everywhere.

5. Enough drivers will be available to continue current levels of production.
   ○ While there have been concerns about a driver shortage, the Bureau of Labor Statistics has reported that there is no reason to believe that the supply of drivers will not meet the demand in the trucking industry [8].
6. Diesel and electric vehicles will follow a template model based upon online research.
   ○ The model is simplified if we assume all electric and diesel vehicles have the same specifications, making the generalization of data easier.
7. Companies use DC Fast Charging (DCFC).
   ○ Economic efficiency needs to be maximized, so the fastest charging option needs to be used for the model.

Model Diesel Vehicle

Characteristic	Assumed Value, with Justification					
Gas Mileage (mpg)	5.98 mpg [1]					
Fixed Cost ($)	$125,000 [10]					
Variable Cost ($)	$1.51 per mile					
Lifetime Range (miles)	We calculated a weighted average of lifetime ranges to serve as the lifetime range of our model diesel vehicle to maintain simplicity.					
	Type	**Annual Mileage**	**Lifetime**	**Lifetime Mileage**	**Proportion of Semis**	**Product**
	SH	42,640	12	511,680	0.05	25,584
	RH	70,000	12	840,000	0.45	378,000
	LH	118,820	12	1,425,840	0.50	712,920
				Weighted Avg		1,116,504

Model Electric Vehicle

Characteristic	Assumed Value, with Justification
Battery Size *(kWh)*	800 [9]
Energy Efficiency *(kWhpm or kWh per mile)*	2 [1]
Max Range (mi)	400 mi Calculated from 800 kWh / 2 kWh per mile. This value also seems to lie between reported ranges from Tesla (600 mi) and Daimler (200 mi) and thus should serve as a good estimate for the total population [1].
Efficient Range (mi)	240 mi

	To maintain battery health, the vehicle should only be charged to 80% and drained to 20%, meaning only 60% of the battery is available for use, and therefore only 60% of range is available. 0.6 * 400 = 240 [1].
Charging Time (hr)	Charging rate for DC Fast Charging (DCFC) is 120 kW [9]. We then calculate the charging time as follows: $$0.6 \times 800 \; kWh \; / \; 120 \; kW \; = 4 \; hrs.$$ LH trucks drive 460 miles per day, RH trucks drive 300 miles per day [1]. Level 2 chargers charge at a rate of 19.2 kW per hour, meaning they replenish around 10 miles of range per hour [9]. This would then require 46 hours to replenish the range for LH trucks, and 30 hours for RH trucks. It will thus be infeasible for a Level 2 charger to replenish enough of the battery drained in a reasonable time frame. DCFC chargers can charge at 120 kW, replenishing around 60 miles of range per hour [9]. This would allow for trucks to be fully recharged in 4 hours. This makes it possible for these trucks to still operate on a daily basis.
Fixed Costs	$180,000 This value is Tesla's projected price for their longer-range vehicle is the estimated cost we found and chose to use. We did not use the price for the smaller range vehicle because it does not seem feasible for it to drive RH and LH routes in the necessary time frame. We neglect charger costs because we consider them a one-time purchase.
Variable Costs	$1.26 per mile [10]
Lifetime Range	The stated lifetime range for the Tesla Semi is 1 million miles. We assume all other vehicles of this type have similar lifetimes. [5]
Lifetime (yrs)	Assuming approximately equal driving rates, and knowing that it takes a normal diesel truck 12 years to drive ~1.1 million miles, we can compute the lifetime of an electric truck to be $$12 \; \times \frac{1,000,000}{1,116,504} = 10.7 \approx 11 \; years.$$

Cost Analysis

Noting that the two vehicles have comparable lifetime ranges, we can calculate the total costs over 1 million miles (one lifetime) for both vehicles. For diesel semis, the cost is given by

$Total\ Cost\ =\ Fixed\ Costs\ +\ Variable\ Costs\ =\ 125,000\ +\ 1.51\ \times 1,000,000$
$= 1,635,000.$

For electric semis, the cost is given by

$Total\ Cost\ =\ Fixed\ Costs\ +\ Variable\ Costs\ =\ 180,000\ +\ 1.26\ \times 1,000,000$
$= 1,440,000.$

Given that electric semis save almost $200,000 by this computation (a fact supported by Tesla's own statement [5]), trucking companies are justified in switching to electric vehicles if the infrastructure is already in place. **This allows us to ignore the differentiation between SH, RH, and LH vehicles; it is economically advantageous to replace all of them. Thus, we construct our model assuming that trucking companies will purchase all available electric vehicles and that they have the revenue to do so. The limiting constraint then becomes the production of electric vehicles.**

Because every diesel truck has a lifetime of 12 years, we can take the sum of the production of trucks over the previous 12 years to find the expected number of semis in any given year. Doing so produces the following values for total truck numbers [11]:

| Year	Estimated Total (RH + LH)	Year	Estimated Total (RH + LH)
2010	1,519,764	2015	1,700,610
2011	1,448,211	2016	1,670,822
2012	1,462,287	2017	1,619,790
2013	1,526,955	2018	1,610,017
2014	1,603,014	2019	1,734,721

Viewing the numbers from 2014 to 2019, we can see that the total number of semis has relatively stabilized over the past few years between 1.6 and 1.7 million. **As a result, we assume that the production of semis simply matches the total number of trucks being retired each year. This means that the estimated production in year *n* is equal to the production in year *n - 12*. Through this, we also assume that the total number of trucks remains constant.**

E. The Model

Modeling the Predicted Production of Electric Semis

There is no hard information on the production of electric semi trucks. Tesla claims it will produce 100,000 trucks per year by 2024, which it will then produce at a steady rate. At the same time, Tesla will clearly not be the only producer in this industry. It is unknown what percentage of the market will be occupied by Tesla, so we assume that the proportion will be similar to the market share it occupies for electric vehicles. This is given to be 53.79% [12]. Using this, we estimate that the peak production of electric semis will be around 100,000 / 0.5379 = 186,000 trucks per year.

In order to model the estimated growth of production in electric semis, we base our prediction on the growth of sales of the Tesla Model 3. This is because Tesla already has some infrastructure in place to produce these semis, just as it already had some infrastructure in place to produce the Model 3.

Production of Model 3 vs Economic Quarters Past 2017 Q3
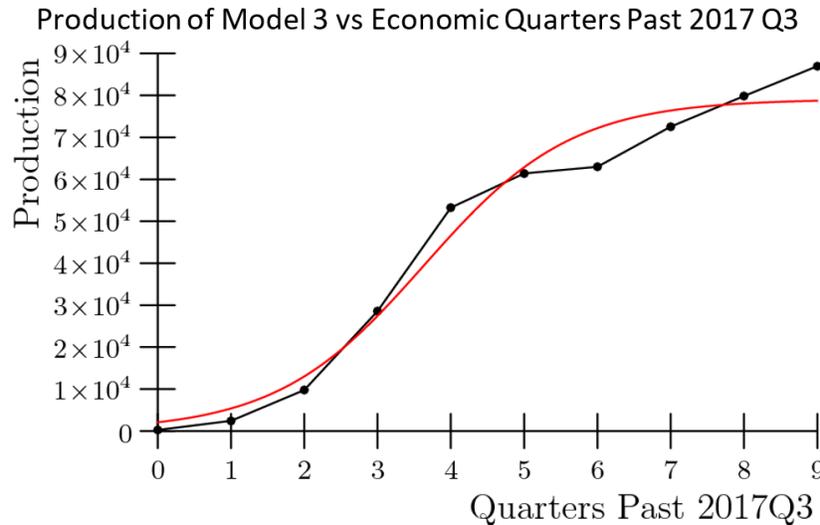
The data set suggests a logistic relationship, concurrent with Musk himself [13]. The computed regression equation is

$$quarterProduction(q) = \frac{79,100}{1 + 37.02e^{-0.993q}}.$$

where q is the number of quarters elapsed past 2017 Q3.

We assume that the production of electric semis follows a similar trend. In order for us to compute this trend, we rely on Musk's claim on being able to reach a steady state production of 100,000 in four years [13].

Fitting the Curve to Our Purpose

We apply dilations to the given curve in order to produce one that reaches steady-state production in its 16th quarter (4th year) and reaches a maximum of 100,000 trucks per year (25,000 per quarter). This is computed as follows:

Changing Maximal Production
$$quarterProduction(q) = \frac{25,000}{1 + 37.02e^{-0.993q}}.$$
It is well known that the numerator of a logistic function is its limit.

Changing Time to Reach Steady State

We note that the Model 3 production has approximately reached its steady state in its 9th quarter. In order for our model to reach it in its 16th quarter, we make the substitution $q \rightarrow 9q/16$:

$$quarterProduction(q) = \frac{25,000}{1 + 37.02e^{-0.993(9q/16)}} = \frac{25,000}{1 + 37.02e^{-0.559q}}.$$

Changing Starting Time

We assume that this growth begins at 2020 Q1 instead of 2017 Q3. Thus, q now reflects the number of quarters past 2020 Q1.

As noted previously, Tesla's market share for electric semis is assumed to be the same as its market share for EVs, which is 53.79%. This then makes the production function equal to

$$quarterProduction(q) = \frac{25{,}000}{1+37.02e^{-0.559q}}/0.5379 = \frac{46{,}477}{1+37.02e^{-0.559q}},$$

q is quarters elapsed from 2020 Q1.

Results of Fitting
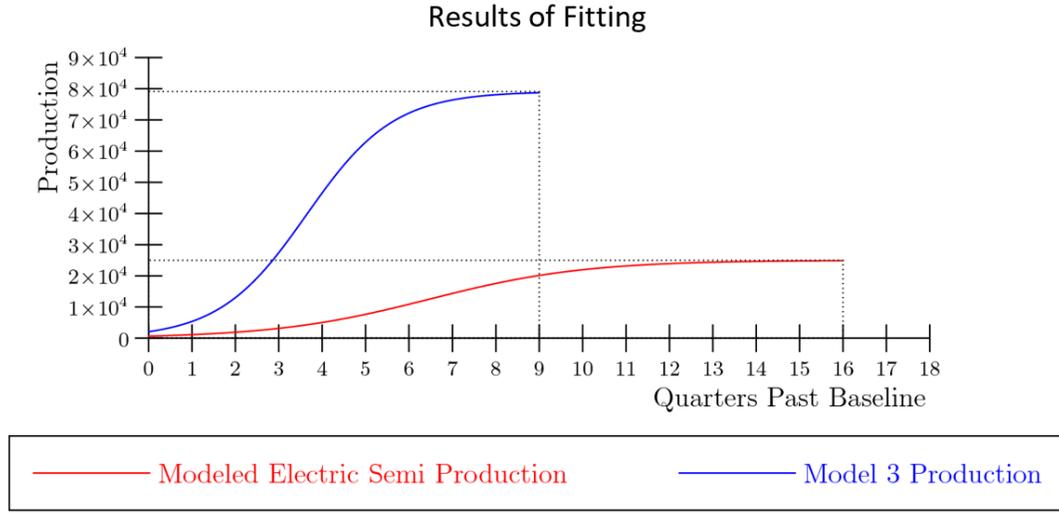
As seen in the graph, the modeled growth of Semis now reaches its steady state of 25,000 at 16 quarters.

We seek yearly production, which would then be computed as the sum of four quarters of that year. Then for year *y*, where *y* is the number of years past 2020 (since we begin modeling from 2020), the annual production is given as follows:

$$annualProduction(y) = \sum_{q=4y}^{4y+3} quarterProduction(q).$$

With this, we can start the computation of our model.

Defining Variables
The following variables are defined for the year *n*.
- Let $prod_d(n)$ be the total number of diesel cars produced. We compute this for years prior to 2020 by taking the sum of RH and LH production given in the [11] and dividing by 0.95, since this only accounts for 95% of total diesel cars (the remaining 5% are SH). For years past 2020, we compute it through the relations below.
- Let $maxprod_e(n)$ be the maximum production of electric vehicles possible in the year, which is given by our $annualProduction$ function. We call this the *maximum* production because, in some cases, the production given by our $annualProduction$ function exceeds the number of cars which go out of service in a given year. Because we expect production companies to then lower their production in that year if their supply begins to exceed demand, we do not consider the companies having leftover inventory.
- Let $e_d(n)$ be the number of diesel semis which go out of service (**e**xpire).
- Let $e_e(n)$ be the number of electric semis which go out of service.
- Let $sold_e(n)$ be the total number of electric vehicles sold.
- Let $serv_e(n)$ be the total number of electric vehicles in service.
- Let $p(n)$ be the proportion of vehicles which are electric.

Relations

We can then define the following relations.

- $maxprod_e(n)$ is given by our $annualProduction$ function.
- $e_d(n) = prod_d(n - 12)$ -- Because the lifetime of a diesel truck is 12 years, every truck produced 12 years prior to the current year should go out of service.
- $e_e(n) = sold_e(n - 11)$ -- Because the computed lifetime of an electric semi is 11 years, every truck produced 11 years prior to the current year should go out of service.
- $sold_e(n) = min(e_e(n) + e_d(n), maxprod_e(n))$ -- If $maxprod$ is less than the total number of vehicles going out of service, then all will be purchased. Otherwise, trucking companies will only purchase the number they need to maintain their current fleet, meaning the number sold will be equal to the sum of expiring electric and diesel vehicles.
- $serv_e(n) = serv_e(n - 1) + sold_e(n) - e_e(n)$ -- The total number of electric vehicles in service is the number in service the previous year plus the number sold in the current year, then minus the number that have gone out of service in the current year.
- $prod_d(n) = e_e(n) + e_d(n) - sold_e(n)$ -- The number of diesel cars produced should be equal to the leftover demand, meaning that if there were not enough electric vehicles sold, the remaining purchased will be diesel.
- $p(n) = serv_e(n)/total\_num$, where $total\_num$ is computed by taking the total production of RH and LH cars in 2019 (1,734,721) and dividing it by 0.95, yielding 1,826,022.

Iterating through these functions then produces the necessary values for our predictions (years starting from 1999 used for calculations, omitted for brevity).

Year	Diesel		total_num	Electric				
	$prod_d(n)$	$e_d(n)$		$maxprod_e(n)$	$sold_e(n)$	$e_e(n)$	$serv_e(n)$	$p(n)$
2020	85,618	98,353	1,826,022	12734	12734	0	12734	0.007
2021	2,792	73,394	1,826,022	70602	70602	0	83336	0.046
2022	0	86,495	1,826,022	153992	86495	0	169831	0.093
2023	0	153,223	1,826,022	181661	153223	0	323054	0.177
2024	0	163,073	1,826,022	185441	163073	0	486126	0.266
2025	0	145,856	1,826,022	185858	145856	0	631982	0.346
2026	1,565	187,467	1,826,022	185903	185903	0	817885	0.448
2027	28,581	214,488	1,826,022	185908	185908	0	1003793	0.550
2028	0	130,823	1,826,022	185908	130823	0	1134616	0.621
2029	0	146,265	1,826,022	185908	146265	0	1280881	0.701
2030	31,868	205,042	1,826,022	185908	185908	12734	1454055	0.796
2031	106,237	221,543	1,826,022	185908	185908	70602	1569361	0.859

2032	0	85,618	1,826,022	185908	172113	86495	1654980	0.906
2033	0	2,792	1,826,022	185908	156015	153223	1657772	0.908
2034	0	0	1,826,022	185908	163073	163073	1657772	0.908
2035	0	0	1,826,022	185908	145856	145856	1657772	0.908
2036	0	0	1,826,022	185908	185903	185903	1657772	0.908
2037	0	0	1,826,022	185908	185908	185908	1657772	0.908
2038	0	1,565	1,826,022	185908	132388	130823	1659337	0.909
2039	0	28,581	1,826,022	185908	174846	146265	1687917	0.924
2040	0	0	1,826,022	185908	185908	185908	1687917	0.924

F. Solution(s)

Our model predicts in column p(n) that in 5 years, the proportion of semis which are electric will be 0.346; in 10 years, it will be 0.796; in 20 years, it will be 0.924.

G. Justification of the Model

Looking at $maxprod_e(n)$, we see that it increases to a steady value by 2024, which matches Musk's predictions [13]. This value is also equal to the one we predicted using Tesla's market share and Musk's stated production goal of 100,000 vehicles per year.

The model increases slowly at the beginning, which makes sense considering the production of electric semis had not yet caught up with demand. It increases quickest between 5 and 10 years, when production has exceeded demand, and many diesel vehicles are being replaced with electric semis. Instances like this are common occurrences when new products garner significant interest and thus spike in sales in certain sectors because of their growing popularity. Finally, as the market begins to become saturated with electric vehicles, the majority of vehicles being replaced each year are electric semis and very few are diesel, so the proportion slows once again.

H. Discussion of Model

Near the end of the predicted values, we see the proportion of electric vehicles begin to stagnate. This is due to the life cycles of diesel and electric semis. The proportion only changes when a sizable number of diesel semis are replaced with electric ones. In some years, all vehicles replaced are electric vehicles; in such cases, p(n) does not change. p(n) begins to stagnate when certain years of diesel trucks are stuck in the fleet, and their life cycle must be completed before they can be replaced.

Ultimately, the model predicts that, given all infrastructure is completely prepared for a seamless transition to electric semis, in 5 years, the proportion of semis which are electric will be 0.346; in 10 years, it will be 0.796; in 20 years, it will be 0.924. This implies that, if this infrastructure were truly in place today, the takeover of electric semis would be swift.

Due to the lack of hard data on the production of electric semis, our estimations for production lack rigor. It scaled the trend of production for Tesla Model 3s to electric semis, which is not necessarily accurate. Having the facilities to produce cars does not imply that they are prepared to produce trucks at the same pace. We also made the assumption that truck

production would reach equilibrium, which would mean that the total number of trucks would remain constant each year. However, it is clear that the production of trucks is slowly increasing, though it remains cyclic due to the lifetime of diesel trucks. Therefore, this assumption neglects the potential growth in the trucking industry.

We investigated economic models for the introduction of substitute goods. If given more time for our model, we would like to research these models in more depth and see if we could apply them to this problem. This would then no longer necessitate the assumption that all new purchases would be of electric vehicles, and would create a far more accurate solution. Additionally, Tesla stated that the production of their Semi would begin this year. Access to these numbers would give us real data on which to base our model for their production.

I. Sensitivity Analysis

We write a generalized form of our production function. We vary the parameters *K, A, r.* Our standard values are as follows:

$$Production = \frac{K}{1+Ae^{-rt}},$$
$$K = 46{,}477, \quad A = 37.02, \quad r = 0.559.$$

Modifying these variables produced the following changes:

Variable	% Change Resulting From 10% Increase			% Change Resulting From 10% Decrease		
	5 Year Pred	10 Year	20 Year	5 Year Pred	10 Year	20 Year
K	0.64%	2.86%	1.96%	-1.32%	-4.32%	-3.62%
A	-0.77%	-0.26%	0.29%	0.64%	0.19%	-0.24%
r	0.67%	0.19%	-0.25%	-2.16%	-0.85%	0.81%

Small changes in these variables produced similarly small changes in predictions. This indicates our model is not highly sensitive, giving us more faith in its predictive power. Changing the max production *K* directly increased the proportions, as expected, while changing *A* and *r*, two growth factors, had differing effects on predictions. This, too, is expected, since they alter the shape of the graph in different ways.

II. Problem #2

A. Background

Major freight corridors mapped by Federal Highway Administration (FHWA) span the entire country, with most corridors concentrated in the eastern hemisphere of the U.S. [14]. The given corridors span many hundreds of miles, meaning that any electric semi would need to charge at least once per trip. Currently, charging stations on the road are predominantly Level 2 and DC Fast Charge sources [15]. Considering an instant switch from LH diesel semis to electric semis, charging times would need to be minimized in order to maximize time efficiency of transportation, meaning that all electric semi chargers would need to be DCFC.

B. Definitions
1. <u>AADT</u>: abbreviation for annual average daily traffic, representing the number of vehicles crossing a set point per day; includes AADTT

2. AADTT: abbreviation for annual average daily truck traffic, representing the number of vehicles considered "trucks" crossing a set point per day (all of these trucks may not be class 8 LH semis)
3. Corridor: generally straight path from one destination to another where semi trucking occurs

C. Restatement of the Problem

To replace diesel semis with electric ones there will need to be charging infrastructure developed for those trucks. We must create a mathematical model to determine the number of charging stations along trucking routes around the nation, based on the 5 corridors provided and their traffic data. To do this, we are considering placing stations along a route based on distance and the amount of chargers per station based on the amount of peak traffic received at that certain point. When considering the distance between stations along each route we are accounting for the worst-case scenario where our electric semi comes onto the route with only 20% available battery charge.

D. Assumptions and Justifications
1. All electric semis follow the same line of specifications as the model electric semi outlined in Problem #1.
   ○ This makes sure that the model stays simplistic enough to determine the number of stations and chargers, based on one model vehicle.
2. All class 8 semis will be considered LH in this model.
   ○ All semis will be going the longest trucking distance, which lets us plan for the worst-case scenario where the trucks are pushed to their limits when considering range.
3. Battery drainage is only a function of the distance traveled, not by the travel time.
   ○ While factoring in the amount of energy taken to accelerate from lower to higher speeds is important for diesel engine calculations due to the relative low RPM and torque value for optimal efficiency, this calculation is less significant in electric vehicles due to the high upper range of optimal RPM and torque. Thus, increased energy consumption is only a factor in electric vehicles when the vehicle undergoes extremely high accelerations, which should not occur.
4. Electric semi batteries should only charge from 20% to 80% of maximum battery capacity.
   ○ This was justified in our model electric truck in Problem #1.
5. Charging follows a strict, fluid schedule.
   ○ After calculating the charging time for 20% to 80% battery, we assume that there is no extra time added in charging a semi and passing off the charger to another semi. This allows for the most efficient allocation of chargers at stations.
6. Traffic data at each mile marker can be averaged to arrive at an estimate of the number of LH semis on the road for one day.
   ○ Semis can enter the corridor from any of the mile markers. Each semi that enters the corridor is likely to be traveling along the corridor route. By averaging the traffic data at all of the mile markers, we avoid the assumption that all semis start at the beginning of the corridor.
7. Trucks are uniformly distributed down the corridor.

○ Each charging station will receive similar traffic, which allows us to place the same amount of chargers at each station to simplify the model.
8. Peak traffic in a single hour has an average of 8% of the total AADT.
○ This was found by analyzing peak traffic data found from the California Traffic Census program on Interstate I-5.

E. The Model

Variables and Constants

Variable or Constant Name	Description, with Justification
$n_{station}$	number of stations required on a route of a certain distance (minimum of 2, one at the starting point and ending point of the corridor)
$n_{charger}$	number of chargers required per station in order to meet maximum traffic
chargetime (*hours*)	4 (time it takes for our modeled electric semi to charge 60% of its battery, calculated in our solution to Problem #1)
dist (*mi*)	total distance from the start and end point of the corridor
onroad	number of class 8 semis on the highway in one day
corridor	string name representing the corridor path from which traffic data is inputted
peakratio	0.08 [16] constant represents the average percentage of the AADT that travels through a point during the peak hours of traffic
percent$_{class8}$ (*per AADTT value*)	$\frac{251{,}000 \; Class\; 8\; Trucks\; sold\; in\; 2018}{709{,}000\; Trucks\; sold\; in\; 2018} = 32\%$ [17] constant represents the ratio of AADTT vehicles that can be classified as LH semis
Battery$_{max}$ (*mi*)	240 (justified under Problem #1's model electric vehicle) constant represents the mileage that could be achieved with the battery standards set in Assumption #4
Battery$_{min}$ (*mi*)	40 (justified under Problem #1's model electric vehicle) constant represents the critical ratio of charge remaining in the semi's battery which the semi should never fall under (meaning that any semi at or below 0.2 charge ratio should immediately seek a charging station to recharge)

According to Assumption #4, the drivers of electric semis should look to charge when the battery reaches 20% capacity. As a protective cushion, we set the minimum charge ratio to be

0.1, so this implies that all semis never fall below 10% capacity. However, some semis can enter the corridor at 20% capacity looking to charge, so the maximum distance to a charging station should be around the mileage that 10% of the charging capacity can achieve, or 80 kWh (40 miles). With this critical distance, we can find out how many stations are needed along a route which is given by

$$n_{station} = \lceil 2 + \frac{dist}{battery_{max} * 0.1}\rceil.$$

Per Assumption #6, we can average the AADTT values for each mile marker. AADTT values published by the FHWA encompass Class 4-13 vehicles, which are all types of trucks based on the FHWA 13-category vehicle classification [18]. We assign the fraction of Class 8 trucks (LH) to all trucks to the **percent_class8** value. This will help us accurately determine the electric semis, not total trucks, on the highway. The AADTT value for each route was found by averaging the given AADTT values compared to the given AADT values to find a ratio of AADTT:AADT. This ratio was then applied to find the missing AADTT values on all routes except for Los Angeles to San Francisco, where all of the values were supplied. Our equation for finding the amount of trucks on the road is given by

$$onroad = percent_{class8} * \underline{mean}(AADTT).$$

We want to have enough chargers to accommodate the peak traffic of the average day. On Interstate 5 in California, the peak ratio of total cars in one hour is 8%. To account for the worse-case scenario, we can extend the peak ratio of cars last for one entire charge cycle. This means that a fraction of trucks that are on the corridor through the charge window will need charge. To determine this fraction of semis, we calculated the decimal number of charges that would be needed per semi per trip down the corridor. For example, for a 240-mile trip, only one charging instance is required. We multiply the fraction of charges over the number of stations to arrive at the number of semis requiring charge in this time frame, which is multiplied to the number of trucks near each station to get the number of chargers needed at each station. The equation to find the number of chargers per station is given by

$$n_{charger} = \lceil \frac{(peakratio * chargetime) * onroad}{n_{station}} \times (\frac{\frac{dist}{battery_{max}}}{n_{station}})\rceil.$$

F. Solution(s)

Testing on all five of the corridors, we arrive at these results for the values of **n_station** and **n_charger** displayed alongside the distance of each corridor route.

Corridor	n_station	n_charger	Corridor Distance (mi)
Los Angeles to/from San Francisco	12	16	382
Boston to/from Harrisburg	12	15	383
Minneapolis to/from Chicago	13	12	421
San Antonio to/from New Orleans	16	17	533
Jacksonville to/from Washington, D.C.	20	9	701

G. Justification of the Model

Based on our model, $n_{station}$ is directly proportional to distance and $n_{charger}$ is directly proportional to the number of Class 8 vehicles traveling through each trucking corridor. Both of these associations make intuitive sense. More charging stations are required as the corridor distance increases, as the trucks now have to travel longer and therefore need more stops. More chargers at stations are required as the number of electric semis on the corridors increase, as each charging station needs to accommodate more electric semis at one time.

H. Discussion of the Model

Our model relies on the minimization of the number of stations and chargers based on edge case values for recharging. The number of stations and chargers is a conservative estimate, given that we expect every one of them to be at full capacity during a prolonged peak traffic period. However, because we prolonged the peak hour for traffic to all four hours, we are still overestimating the number of total chargers we would need along the route at one time. This overestimation could result in increased fixed costs, delaying station implementation, or inefficient station activity, resulting in wasted resources for return. However, a model that overestimates the number of stations and chargers needed is better than a model that underestimates the number of stations and chargers, which could lead to disastrous battery shortages along the trucking corridors.

Charging an electric semi is significantly more time-consuming than refueling a diesel semi. However, because $battery_{max}$ is 240 miles, and LH semis drive an average of 457 miles per day, approximately two charges a day are needed [11]. Since truck driver regulations state that a driver may be on duty for 14 hours a time with a maximum of 11 hours of driving time, a 3 hour break can be inserted into each driver's day [1]. This allows for a window to charge the vehicle as the driver takes a break. When the driver retires for the night, another charge can be done. This conveniently makes for the least amount of wasted time waiting for the vehicle to charge. Employees managing the charging station would have to remove the vehicle from the charger when it is finished charging to allow for other vehicles to use the charger as well.

A weakness of our model is that not all situations are able to be considered. For example, some months out of the year may result in a lot more semis on the road because of holiday shopping and other days with abnormally high numbers of semis on the routes. This would cause a higher AADTT than our average, which would cause backups in the charging stations.

I. Sensitivity Analysis

AADT and AADTT are both average traffic data values. There is natural sampling variation where, on certain days, the number of LH semis on the highway is drastically greater or less than the average. We are mainly concerned about the days with increased semi presence, because a shortage in chargers is more harmful than an excess. Trucks that would have to wait mean that economic efficiency is decreased. In a future model, the right tail of traffic times could be accounted for by approximating the sampling distribution with the Normal Model in order to calculate a greater edge case, accounting for the days with the highest traffic volume.

III.   Problem #3

A. Background

The integration of electric semis in the trucking industry will occur gradually and only in areas where there is sufficient support, minimal costs, and a desire to reduce carbon emissions. While many companies have already placed orders for Tesla's Semis (Walmart, PepsiCo, Sysco), the location for their operation has not been stated by most companies [19]. PepsiCo, one of the largest buyers, is currently analyzing which routes present the best opportunity for operation, considering things like payload and length of the route [20]. To ensure proper integration of electric semis, it is important that the corridors used are optimized for electric semi use.

B. Definitions
1. FCEV: abbreviation for fuel-cell electric vehicles running on electricity generated by hydrogen fuel
2. BEV: abbreviation for battery electric vehicles running exclusively on electric fuel
3. PHEV: abbreviation for plug-in hybrid electric vehicle running on either or both gasoline and electric fuel

C. Restatement of the Problem
In order to accommodate electric semis, traditional trucking corridors must be modified to accommodate the new technology. We must create a mathematical model to determine which trucking corridors are going to transition to accommodate electric semis first. To do this we are considering factors such as public support of electric semis, environmental impacts such as carbon emissions, and economic development. We will factor all of these variables to create a Monetary Transition Index value that would be used to determine the order of implementation.

D. Assumptions and Justifications
1. The sampling data for each parameter can be approximated using a Normal Model.
   - Although our data is not specified to be random, we can assume they are representative of the parameters in question. Although the sample is more than 10% of the entire population, each state and corridor has their own laws and regulations, and thus we can assume that the parameters for one state or corridor don't affect the value of other states' or corridors' parameters. Thus, all conditions are satisfied to apply the Central Limit Theorem and convert the sampling data into individual z-scores for modeling purposes.
2. Each of the four parameters are weighted equally.
   - The relative importance of each parameter is subjective. Some companies and states may consider environmental impacts the most important, while others may value public opinion. For the purposes of simplicity, we assigned each parameter equal weight for the Transition Index, adding neutrality to our model.
3. Environmental impacts can be modeled solely through carbon emissions.
   - For diesel engines, the largest impact on the environment is carbon emissions caused by their exhausts. These carbon emissions contribute to climate change much more than any other impact the truck may have on the environment as it produces emissions over its entire lifespan instead of just at production and other pollutants produced during operation are minimal.
4. All people who buy a plug-in hybrid, fuel cell, or fully electric vehicle support the integration of electric semis.

- ○ Since these people have already purchased electric or partly electric vehicles they would support the implementation of electric semis into the trucking business.
5. All diesel trucks currently on the road produce the same amount of carbon emissions.
   - ○ The average weight of each truck payload is 37800 lbs, and each truck produces approximately the same level of emissions to match government standards.
6. The cost to build one charger that charges at 120 kwh is $25,000.
   - ○ This was found from the cost of a 75kwh charger being $15,000 to develop (battery data sheet). The cost of building multiple charging stations along a route that add up to hundreds of chargers can dramatically affect the ability of a company to establish the infrastructure for electric semis. The number of chargers along each route is provided by our model in Problem #2.

E. The Model

The Model's Four Factors of Consideration

Factor	Description
Public Support (PS)	Estimated support for the project by the general population. The more public support there is, the more likely the government will be to pass legislation facilitating the development of charging stations along the corridors.
Carbon Emissions Cost (CEC)	The cost assigned to carbon emissions from diesel semis traveling along this route.
Projected Development Cost (PDC)	The cost of the supercharging stations required for the routes to be compatible with electric semis.
Usage (U)	The amount of semis that travel along the trucking corridor is given by the AADTT.

Public support was approximated using the method described in Assumption #4. Through this assumption, the owners of plug-in hybrid, fuel cell, or fully electric vehicles serve as a proxy to approximate general support for electric vehicles and thus electric semis. Using the market share percentage of electric vehicles, plug-in hybrids, and fuel-cell electric vehicles from the Alliance of Automobile Manufacturers, the market shares are given weighting according to the state population (given by Census Bureau estimates for 2019) to find public support. This is given by

$$PS = \frac{\Sigma \ (\%Market \ Share \ in \ State) * (Population \ of \ State)}{Total \ Population \ of \ State \ Along \ Route}.$$

Corridor	Market Share of FCEV, BEV, PHEV (%) [21]	Population (# of residents) [22]	Public Support (% Market Share Over Route)
San Antonio, TX to/from New Orleans, LA	TX: 0.37 LA: 0.15	TX: 28,995,881 LA: 4,648,794 Total: 33,644,675	0.340
Minneapolis, MN to/from	MN: 0.59	MN: 5,639,632	0.593

Chicago, IL	WI: 0.56 IL: 0.61	WI: 5,822,434 IL: 12,671,821 Total: 24,133,887	
Boston, MA to/from Harrisburg, PA	MA: 1.12 CT: 1.09 NY: 0.81 PA: 0.50	MA: 6,892,503 CT: 3,565,287 NY: 19,453,561 PA: 12,801,989 Total: 42,713,340	0.790
Jacksonville, FL to/from Washington, DC	FL: 0.56 GA: 1.18 SC: 0.28 NC: 0.53 VA: 0.76	FL: 21,477,737 GA: 10,617,423 SC: 5,148,714 NC: 10,488,084 VA: 8,535,519 Total: 56,267,477	0.676
Los Angeles, CA to/from San Francisco, CA	CA: 4.61	CA: 39,512,223 Total: 39,512,223	4.61

Using California's current price per metric ton of carbon emissions, $15, as well as the average carbon emissions of class 8 diesel semis across day and sleeper cabs with low, medium, and high roofs -- 79.58 *grams per ton-mile* -- and the average weight of payload carried by trucks, 18.9 *U.S. tons*, the cost of carbon emissions was calculated [23, 24, 25]. Since these carbon emission costs would be subtracted by development of electric semi transport, these dollar values remained positive. This is given by

$$Carbon\ Emission\ Cost\ Per\ Mile\ (CECPM)\ = \frac{\$0.015}{kg\ CO_2} \times \frac{0.07958\ kg}{ton-mile} \times 18.9\ U.S.Ton\ =$$
$$\$0.0226\ per\ mile,$$
$$Carbon\ Emission\ Cost\ =\ CECPM\ \times\ Length\ of\ Route.$$

Corridor	Route Length (miles)	Carbon Emissions (U.S. Dollars)
San Antonio, TX to/from New Orleans, LA	533	218,511
Minneapolis, MN to/from Chicago, IL	421	105,336
Boston, MA to/from Harrisburg, PA	383	107,737
Jacksonville, FL to/from Washington, DC	702	174,904
Los Angeles, CA to/from San Francisco, CA	382	120,648

The usage of each corridor is given by the AADTT for each route (corridor_data), which

was calculated in Problem #2. This allows us to consider the amount of trucks on each route to see which route would affect the most truckers.

Corridor	Usage (AADTT)
San Antonio, TX to/from New Orleans, LA	18,140
Minneapolis, MN to/from Chicago, IL	11,071
Boston, MA to/from Harrisburg, PA	12,447
Jacksonville, FL to/from Washington, DC	11,024
Los Angeles, CA to/from San Francisco, CA	13,975

Each charging station has several chargers that cost around $25,000 each to produce and install (battery data sheet). Multiplying the number of stations with the number of chargers in each station gives us the number of chargers on each route. Then multiplying the number of chargers with the cost of one charger gives the total cost of developing the whole route. The values are negative because it has a negative effect on the development of the route.

$$Cost = \frac{\#Chargers}{Station} \times \#Stations \times \frac{-\$25000}{Charger}.$$

Corridor	Total Charging Stations	Chargers per Station	Cost
San Antonio, TX to/from New Orleans, LA	16	17	-6,800,000
Minneapolis, MN to/from Chicago, IL	13	12	-3,900,000
Boston, MA to/from Harrisburg, PA	12	15	-4,500,000
Jacksonville, FL to/from Washington, DC	20	9	-4,500,000
Los Angeles, CA to/from San Francisco, CA	12	16	-4,800,000

The final step was to standardize the factors of consideration by replacing each value with a z-score, with the sample being the values for each of the 5 corridors. The scores were then added for each route to produce a final index score.

Corridor	PS (% of pure EV cars)	CEC	PDC	U	Monetary Transition Index Score
TX-LA	-0.59	1.47	-1.71	1.63	0.80
MN-IL	-0.45	-0.81	0.90	-0.77	-1.12
MA-PA	-0.34	-0.76	0.36	-0.30	-1.04

FL-DC	-0.40	0.59	0.36	-0.78	-0.23
CA-CA	1.78	-0.50	0.09	0.22	1.59
AVG	1.40	145,427.10	-4,900,000	13,331	
STD DEV	1.80	49,628.52	1,111,305.54	2,947.50	

F. Solution(s)

The Monetary Transition Index Score column of the above table of standardized scores represents the final score assigned to each route. The highest score, 1.59, for the route from Los Angeles, CA, to San Francisco, CA, presents the optimal option for development, followed by the Texas to Louisiana route, the Florida to D.C. route, the Massachusetts to Pennsylvania route, and, last, the Minnesota to Illinois route.

G. Justification of the Model

Considering that California is already of the leaders in electric vehicle usage and production (Tesla HQ is in CA) as well as a hub for several technology based companies, it is understandable that our model predicts that they have significantly higher support for electric semis. For carbon emissions, the model's prediction of the Texas to Louisiana route as having the most to gain from the transition makes sense, considering that it has the second longest length and highest usage. Since the projected economic cost is partially based on the solution to Problem #2, it cannot be fully assured to be accurate; however, it can be reasonably assumed to be at least somewhat representative of the costs associated with building charging stations. Thus, the predictions that this model has made are reasonably accurate with potential to change but not so much as to reverse the order of corridors or alter it drastically.

H. Discussion of the Model

Our model revealed that there are a lot more factors than just economic development cost that affect the development of electric trucking.

Since multiple variables were involved in the model, the final index score rankings did not perfectly follow any of the trends of the four factors of consideration. Outliers (high z-scores) had a significant impact on the final index score. For example, the California route having an extremely high public support value (1.78) and the Texas to Louisiana route having high carbon emission costs, projected economic costs, and usage shifted their index scores significantly. Another weakness of the model was that all of the factors were weighed the same amount. There was no established basis for weighing the four factors, so we standardized the score. If we weighed every factor precisely the index scores would have been more accurate.

If we were able to work on this problem for the next few months we would develop a more accurate cost analysis for the charging stations that takes into account fluctuating electricity costs, differing prices for land use along the different routes, and labor costs. Another factor we would consider is the multiple types of diesel trucks and the weights of payloads they carry to make our carbon emissions more accurate.

I. Sensitivity Analysis

Our results were dependent on several assumptions. If our assumption about equal weighting for standardized scores was changed to a separate weighting system, it could

potentially have a significant effect on the index scores but only if the weighting system gave substantially small or large preference to certain factors of consideration. Concerning carbon emissions, the assumption about carbon emissions modeling overall environmental impact could change. However, most of the impact of vehicles comes from carbon dioxide, and secondary pollutants such as carbon monoxide and volatile organic compounds are emitted in much smaller concentrations (2.395 g/ton-mile and 0.455 g/ton-mile respectively); so including them would not alter the result [26]. If the people who own FCEV, BEV, and PHEV do not actually support electric semis, that would have a significant effect on the public support factor. However, it is unlikely that support would wane that significantly just for a different type of vehicle. Of all the factors, the public support has the largest probability to change. This might change the overall order, but it is unlikely that the California route's #1 position in that ranking will change.

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